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Member contribution-based group recommender system

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ABSTRACT

Developing group recommender systems (GRSs) is a vital requirement in many online service systems to provide recommendations in contexts in which a group of users are involved. Unfortunately, GRSs cannot be effectively supported using traditional individual recommendation techniques because it needs new models to reach an agreement to satisfy all the members of this group, given their conflicting preferences. Our goal is to generate recommendations by taking each group member's contribution into account through weighting members according to their degrees of importance. To achieve this goal, we first propose a member contribution score (MCS) model, which employs the separable non-negative matrix factorization technique on a group rating matrix, to analyze the degree of importance of each member. A Manhattan distance-based local average rating (MLA) model is then developed to refine predictions by addressing the fat tail problem. By integrating the MCS and MLA models, a member contribution-based group recommendation (MC-GR) approach is developed. Experiments show that our MC-GR approach achieves a significant improvement in the performance of group recommendations. Lastly, using the MC-GR approach, we develop a group recommender system called GroTo that can effectively recommend activities to web-based tourist groups.

1. Introduction

Many online services, such as e-commerce, e-government and e-learning, suffer from the information overload problem, i.e. the massive amount of information available for users makes it very difficult to locate the information that users most require [1–3]. Recommender systems are one of the most successful techniques proposed to address this problem through the analysis of user information to model individual preferences and target relevant related information.

Although significant advances have been made to improve recommender systems, most prior recommender system studies have focused on providing recommendations to individual users (a business or a customer). Group recommender systems (GRSs) have been proposed more recently to produce recommendations for groups of users. GRSs must respond to members' up-to-date preferences and produce recommendations to satisfy the whole group. GRSs have been designed and implemented in many service domains. Sharon et al. [4] designed an internet browser GRS which recommends related links for a set of browsers which have a similar navigation history. Another example called GRec_OC, proposed by [5], can recommend textual information and suggest books for an online reading community. Other than textual recommendation, multimedia content can also be recommended. For example, [6] recommends TV programs for a family instead of an individual viewer; [7] can suggest movies for a group of friends; and MusicFX in [8] is designed to play music that suits the tastes of all the people in a gym. An even more complicated situation arises when recommending a tourism plan for heterogeneous tourist groups (such as families with children and elderly) [9].

From the formation perspective, there are two main types of group in GRSs, regardless of system domain: stable groups and random groups [10]. Members of stable groups may actively join or leave groups, and may specify their preferences. In such groups, members become highly internally correlated, so that group preferences can be centralized over time, and items can then be easily found that satisfy every member in the group. For instance, a reading group might narrow the range of reading to ultimately focus on realist novels or poems. In contrast, random groups are passively formed by members who have no opportunity to specify their preferences or negotiate a consensus preference. These random groups may be homogenous and have highly conflicting group preferences; for example, the type of music that should be recommended for all the people at a party.

Most of the work on modeling group preferences in GRSs is based on rating information, which may not be accurate when the rating matrix is sparse or when groups are large. Many researchers have attempted to solve this problem but have only focused on building complex individual preferences by introducing additional information, such as social

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network information, tags or context information, to depict member interaction or personality [7,11–14]. However, there is no generally-accepted additional information available across application domains, and in many scenarios there is no opportunity to access additional information about members in a random group.

The type of group affects the design of the GRS, and a major issue in making recommendations to random groups is the conflict of preferences that arises when members pursue their individual preferences without considering those of other members. This problem worsens when larger random groups are involved, because finding a compromise for diverse interests is more difficult to model, and recommendations are consequently more difficult to produce. An appropriate solution to reduce the conflict is to consider and numerically evaluate the relationships between group and individual members and to model the group profile according to the preferences of the representative members. The preferences of more representative members outweigh those of less representative members, which ensures that GRSs are able to build a high level of compromise between group profiles. However, similar to tackle preference conflicts, most of the work on computing representative preferences requires additional information, such as social relationships or trust networks [15].

This study aims to develop a group recommendation approach which can maximize satisfaction within random groups by modeling preferences through the analysis of contributed member ratings alone. Our proposal measures each member's importance in terms of the sub-rating matrix which makes it practical even when the matrix is highly incomplete and sparse. This approach consists of two main phases: (1) a group profile generator and (2) a recommendations generator. We first propose a member contribution score (MCS) model for Phase 1. In Phase 2, a Manhattan distance-based local average rating (MLA) model is developed to address the fat tail problem by estimating group ratings on a reduced set of items which are close to the target item. By integrating the MCS and MLA models, a member contribution-based group recommendation (MC-GR) approach is developed. Lastly, a group recommender system and its application in online tourist groups is presented.

The contributions of this paper can be summarized as follows:

1) A member contribution-based group recommendation (MC-GR) approach is proposed to tackle the general group recommendation problem in which the group profile is generated according to member contributions, considering only the rating information without the need for additional information. Experimental results show that this approach significantly outperforms comparable baselines.
2) An MCS model is developed to measure member contributions in terms of a sub-rating matrix in which separable non-negative matrix factorization (SNMF) is employed to identify representative members and calculate corresponding contributions to the group profile. The group profile can thus be modeled accurately even when the rating matrix is highly incomplete and sparse.
3) A Manhattan distance-based model is presented to capture the local approximation of the group average rating and improve prediction accuracy, thus alleviating the potential fat tail problem.

The rest of this paper is organized as follows. We review individual recommendation approaches and the key improvements to group recommendation approaches in Section 2. Section 3 presents our MC-GR approach in detail. The experiments and results analysis are demonstrated in Section 4. A group recommender system, GroTo, is developed for web-based tourist groups, and its framework is shown in Section 5. The conclusion and further study are presented in Section 6.

2. Literature review

In this section, we present the two general approaches to generating individual and group recommendations. We review both types of approach, because to aggregate individual recommendations or build a group profile requires knowledge of individual recommendation approaches. We also present several detailed methods related to these approaches, and follow with a discussion of these methods and the limitations of existing methods.

2.1. Individual collaborative filtering-based approaches

Most GRSs allow users to specify their preferences as scalar ratings (e.g. from 1 to 5) or binary ratings (e.g. thumb for posts). Collaborative filtering (CF) techniques [16], which rely on ratings, are widely applied in GRSs. Some advanced individual recommendation approaches [17] are beyond the scope of this paper and will not be introduced; rather, we review the two most popular families of CF recommendation approaches: item-based CF (ICF) and user-based CF (UCF). ICF approaches recommend items similar to a user's previously preferred items [18], while UCF approaches recommend items preferred by people who have common interests. The unknown ranks can be predicted by aggregation methods such as weighted average, average z-score and average deviation from mean [19,20].

2.1.1. Item-based approaches

ICF approaches first measure the pairwise similarities between items. Once these similarities have been obtained, unknown ratings can be predicted and items which are similar to past preferred items can be identified. ICF approaches aim to recommend the top-k closest items, as shown in Eq. (1). We show that, to predict the unobserved rating $r_{u,i}$ for user $u \in U$ of item $i \in I$, $r_{u,i}$ can be estimated by the weighted average of the observed ratings of u weighted by the corresponding item similarities. We can easily make suggestions when u has rated enough items to model their preference.

$$r_{u,i} = \overline{r_i} + \frac{\sum (r_{u,j} - \overline{r_j}) \times Similarity(i, j)}{\sum |Similarity(i, j)|} \tag{1}$$

2.1.2. User-based approaches

By contrast, UCF approaches first measure the similarities between users. The unobserved rating $r_{u,i}$, which is derived from user u for item i, is predicted by ratings from users who share similar preferences to u. The prediction equation is shown in Eq. (2).

$$r_{u,i} = \overline{r_u} + \frac{\sum (r_{v,i} - \overline{r_v}) \times Similarity(u, v)}{\sum |Similarity(u, v)|} \tag{2}$$

ICF and UCF are also called neighbor-based approaches, because they identify similar items or users respectively. Clearly, once we can model a pseudo user whose profile represents the preference of the whole group, the UCF approach can be used to generate group recommendations.

2.2. Group recommendation approach

The group-defining procedure can be active or passive according to the application scenario. Some scenarios allow users to actively announce that they are in a specific group, while in others, users are passively allocated to a group. For example, members in a reading group actively form the group and then obtain book recommendations for all members. On the other hand, when people passively become a group as a result of attending a music show, recommendations for other music shows cannot be determined simply on the basis of that single attendance. In either case, a group recommender system can be defined as R, when it provides generalized items, such as books or music, for system users. The system then determines all the members in the group and makes recommendations for them as a single entity after the group has been formed. We denote all the items in R as I and all the users as U, and a group as G, in which $G \in U$ is a collection of